Simultaneous Optimization of Wind Farm Layout and Cable Routing Using Multi-Objective Evolutionary Algorithms

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Abstract. *Offshore wind farm design requires jointly optimizing turbine placement and electrical cable routing, two decisions that interact through energy production and infrastructure cost. This work formulates the problem as a bi-objective optimization problem, called MoWFLCOP, and evaluates three routing strategies embedded in NSGA-II, SPEA2, and MOEA/D: a sequential approach, an integrated sweep-based strategy, and an extended formulation. Experiments on ten offshore benchmark instances with thirty independent runs show that routing integration is strongly algorithm-dependent. NSGA-II with the integrated strategy outperforms the sequential and extended variants in seven of ten instances. MOEA/D shows limited sensitivity to the routing strategy, while SPEA2 performs better under the sequential approach in most cases. The extended strategy is advantageous only in the most complex instance.*

1. Introduction

Designing offshore wind farms that effectively balance cost minimization with energy production presents a complex challenge, combining combinatorial optimization with real-world engineering constraints [Machado et al. 2024]. As the demand for renewable energy expands, so too does the scale and complexity of wind farm infrastructure, requiring advanced algorithmic approaches capable of addressing interdependent design decisions [Lee and Zhao 2024].

A critical aspect of offshore wind farm design is the optimal placement of turbines to maximize power generation, formulated as the *Wind Farm Layout Optimization Problem* (*WFLOP*). Minimizing the cost of electrical cable connections, defined as the *Wind Farm Cable Routing Problem* (*WFCRP*), is another central objective. Traditionally, these subproblems have been addressed sequentially, with layout optimization preceding cable routing [Cazzaro and Pisinger 2022b, Tao et al. 2021]. While this strategy simplifies implementation, it can lead to suboptimal configurations, since turbine placement directly influences cable routing feasibility and cost.

Recent research has emphasized the benefits of integrated strategies. Cazzaro et al. [Cazzaro et al. 2023] proposed a single-objective MILP model that jointly considers layout and cabling, revealing important trade-offs. He et al. [He et al. 2024] expanded this view with a multi-objective formulation, highlighting the value of treating generation and cost as conflicting goals. However, although recent studies have shown the relevance of jointly considering layout and cable routing decisions, it remains unclear how cable routing information should be incorporated into the search process of multi-objective evolutionary algorithms. In particular, little attention has been given to whether routing should be treated as a post-processing step, embedded as a domain-specific heuristic

during solution evaluation, or explicitly represented and modified by evolutionary operators. Moreover, the impact of these alternatives across different MOEA architectures remains insufficiently understood.

This study addresses this limitation by formulating the *Multi-objective Wind Farm Layout and Cable Optimization Problem* (*MoWFLCOP*), in which turbine placement and cable routing are treated within a unified graph-based representation. Rather than considering routing only as a post-processing step, we investigate how cable routing information should be incorporated into the search process of multi-objective evolutionary algorithms. To this end, we compare three coupling strategies: a sequential strategy, in which routing is computed after layout optimization; an integrated strategy, in which a sweep-style routing heuristic [Cazzaro et al. 2020] is embedded into the evaluation cycle; and an extended strategy, in which routing structures are explicitly represented and modified by crossover and mutation operators.

These strategies are evaluated within three established MOEA architectures: NSGA-II [Deb et al. 2002], SPEA2 [Zitzler et al. 2001], and MOEA/D [Zhang and Li 2007]. This design results in nine algorithmic variants, allowing us to assess not only whether routing integration improves solution quality, but also whether its effectiveness depends on the underlying search mechanism, namely dominance-based selection, strength-based fitness assignment, or decomposition-based optimization. The experimental evaluation is conducted on ten standardized offshore benchmark instances [Cazzaro et al. 2023]. Each variant is independently tuned using irace and executed over multiple independent runs under a fixed evaluation budget. Performance is assessed using a hypervolume-based indicator and nonparametric statistical tests, providing a consistent basis for comparing the impact of sequential, integrated, and extended routing strategies.

The main contributions of this work are threefold: (1) we formulate the MoWFLCOP as a bi-objective optimization problem that jointly considers energy production and infrastructure cost; (2) we compare three strategies for coupling turbine layout and cable routing decisions, namely a sequential strategy, an integrated strategy based on a sweep routing heuristic, and an extended strategy in which routing structures are explicitly modified by evolutionary operators; and (3) we evaluate these strategies within NSGA-II, SPEA2, and MOEA/D, showing that the effectiveness of cable routing integration depends on the underlying MOEA architecture.

2. Related Work

The optimization of offshore wind farms has traditionally been addressed by separating turbine layout and cable routing into two independent subproblems. The *Wind Farm Layout Optimization Problem* focuses on maximizing energy production, while the *Wind Farm Cable Routing Problem* aims to minimize infrastructure costs. Although this separation simplifies the optimization process, it can lead to suboptimal solutions, as layout decisions directly impact cable routing feasibility and cost [Tao et al. 2021, Pérez-Rúa and Cutululis 2021].

To address this limitation, recent studies have proposed integrated formulations that consider layout and cabling simultaneously. Cazzaro et al. [Cazzaro et al. 2023] introduced a unified model combining both decisions within a single optimization framework, although using a single-objective formulation. He et al. [He et al. 2024] extended

this idea to a multi-objective setting, treating energy production and cost as conflicting objectives. Despite these advances, most integrated approaches rely on deterministic or heuristic procedures to construct cable routing solutions during the optimization process.

In the context of multi-objective optimization, evolutionary algorithms have been widely adopted due to their ability to approximate trade-offs between conflicting objectives. Previous work has shown that embedding domain-specific heuristics into evolutionary frameworks can improve solution quality, particularly for cable routing problems [Machado et al. 2024]. However, these approaches typically treat cable routing as a derived structure, reconstructed from the turbine layout at each evaluation.

Less attention has been given to alternative formulations in which cable routing is explicitly represented and evolved alongside turbine layout decisions. Such approaches introduce additional flexibility but also increase the complexity of the search space, raising questions about their effectiveness when compared to heuristic-guided strategies.

In contrast to studies centered on a single MOEA architecture, this work compares dominance-based, strength-based, and decomposition-based algorithms under the same experimental setting. It builds on the observations above by comparing three distinct strategies for handling the interaction between layout and routing decisions: a sequential approach, an integrated heuristic-guided approach, and an extended formulation in which both layout and cable routing are subject to evolutionary operators.

3. Problem Definition

The *MoWFLCOP* addresses the simultaneous selection of turbine locations and electrical cable connections in offshore wind farms. It combines two coupled decision layers: the *Wind Farm Layout Optimization Problem* (*WFLOP*), which determines the spatial distribution of turbines, and the *Wind Farm Cable Routing Problem* (*WFCRP*), which defines how the selected turbines are connected to a substation through feasible cable paths.

The problem has two conflicting objectives: maximizing energy production and minimizing infrastructure cost. Energy production depends on turbine placement and wake interactions, modeled through the Jensen formulation [Shakoor et al. 2016]. Cost depends on both foundation costs and the electrical cable network required to connect the selected turbines.

We use the graph-based formulation of [Fischetti and Pisinger 2018, Cazzaro et al. 2023]. Let $G(V, A)$ be a directed graph, where $V = V_T \cup \{v_0\}$ is the set of vertices, V_T is the set of candidate turbine sites, v_0 is the fixed substation, and $A \subseteq V \times V$ is the set of feasible directed arcs. Each arc represents a possible cable connection, and its direction follows the energy flow from turbines toward the substation. Let $\mathcal{C} \subset A \times A$ be the set of arc pairs that would geometrically cross if selected simultaneously.

Let Γ be the set of available cable types. Each cable type $\gamma \in \Gamma$ has unit cost u^γ and capacity k^γ. The cost of installing cable γ on arc $(i, j) \in A$ is given by

$$c_{ij}^\gamma = u^\gamma \, \mathrm{dist}(i, j),$$

where $\mathrm{dist}(i, j)$ is the Euclidean distance between sites i and j.

Let N_T be the number of turbines to be installed, $D_{\min}$ the minimum distance allowed between installed turbines, F_i the foundation cost at site i, and M a sufficiently large constant. Let $P_{ii} \geq 0$ be the free-stream power at site i, and let $P_{ij} \leq 0$, for $i \neq j$, be the wake-induced power loss at site i caused by a turbine installed at site j. For a layout vector $\mathbf{z}$, the net power at site i is defined as

$$P_i^{\text{net}}(\mathbf{z}) = P_{ii} z_i + \sum_{\substack{j \in V_T \\ j \neq i}} P_{ij} z_i z_j.$$

The decision variables are defined as follows: $z_i \in \{0,1\}$ indicates whether a turbine is installed at site $i \in V_T$; $y_{ij} \in \{0,1\}$ indicates whether arc $(i,j) \in A$ belongs to the cable network; $x_{ij}^{\gamma} \in \{0,1\}$ indicates whether cable type $\gamma \in \Gamma$ is selected on arc $(i,j) \in A$; and $f_{ij} \geq 0$ represents the electrical flow on arc $(i,j) \in A$.

The bi-objective model is defined as:

$$\max \quad Z_{\text{power}}(\mathbf{z}) = \sum_{i \in V_T} P_i^{\text{net}}(\mathbf{z}), \tag{1}$$

$$\min \quad Z_{\text{cost}}(\mathbf{z}, \mathbf{x}) = \sum_{(i,j) \in A} \sum_{\gamma \in \Gamma} c_{ij}^{\gamma} x_{ij}^{\gamma} + \sum_{i \in V_T} F_i z_i. \tag{2}$$

The model is subject to the following constraints:

$$\sum_{i \in V_T} z_i = N_T, \tag{3}$$

$$\text{dist}(i,j) \geq D_{\min} - M(2 - z_i - z_j), \qquad \forall i < j \in V_T, \tag{4}$$

$$\sum_{\gamma \in \Gamma} x_{ij}^{\gamma} = y_{ij}, \qquad \forall (i,j) \in A, \tag{5}$$

$$y_{ij} \leq z_i, \qquad \forall (i,j) \in A,\ i \in V_T, \tag{6}$$

$$y_{ij} \leq z_j, \qquad \forall (i,j) \in A,\ j \in V_T, \tag{7}$$

$$\sum_{j:(i,j) \in A} y_{ij} = z_i, \qquad \forall i \in V_T, \tag{8}$$

$$y_{ij} + y_{hk} \leq 1, \qquad \forall ((i,j),(h,k)) \in \mathcal{C}, \tag{9}$$

$$\sum_{j:(i,j) \in A} f_{ij} - \sum_{j:(j,i) \in A} f_{ji} = P_i^{\text{net}}(\mathbf{z}), \qquad \forall i \in V_T, \tag{10}$$

$$\sum_{j:(j,v_0) \in A} f_{jv_0} = \sum_{i \in V_T} P_i^{\text{net}}(\mathbf{z}), \tag{11}$$

$$f_{ij} \leq \sum_{\gamma \in \Gamma} k^{\gamma} x_{ij}^{\gamma}, \qquad \forall (i,j) \in A, \tag{12}$$

$$z_i \in \{0,1\}, \qquad \forall i \in V_T, \tag{13}$$

$$y_{ij} \in \{0,1\}, \qquad \forall (i,j) \in A, \tag{14}$$

$$x_{ij}^{\gamma} \in \{0,1\}, \qquad \forall (i,j) \in A,\ \gamma \in \Gamma, \tag{15}$$

$$f_{ij} \geq 0, \qquad \forall (i,j) \in A. \tag{16}$$

Constraint (3) fixes the required number of installed turbines, while (4) enforces the minimum spacing between them. Constraint (5) links arc selection and cable type selection. Constraints (6) and (7) ensure that cables are connected only to selected turbine sites or to the substation. Constraint (8) requires each installed turbine to have exactly one outgoing connection. Constraint (9) prevents simultaneous selection of crossing cable arcs. Constraints (10) and (11) enforce power flow conservation toward the substation, and (12) ensures that cable capacities are not exceeded. Constraints (13)–(16) define the variable domains.

This formulation defines a mixed-integer quadratic bi-objective problem. In this work, it is used to define the objectives, decision variables, and feasibility conditions considered by the evolutionary approaches, rather than being solved exactly, since exact optimization becomes computationally expensive for large offshore benchmark instances.

4. Evolutionary Algorithms

We use three well-known multi-objective evolutionary algorithms: the *Non-dominated Sorting Genetic Algorithm II* (NSGA-II) [Deb et al. 2002], the *Strength Pareto Evolutionary Algorithm 2* (SPEA2) [Zitzler et al. 2001], and the *Multi-objective Evolutionary Algorithm based on Decomposition* (MOEA/D) [Zhang and Li 2007]. These algorithms were selected because they are widely used to approximate Pareto fronts in problems with conflicting objectives.

NSGA-II ranks solutions using Pareto dominance and uses crowding distance to preserve diversity. SPEA2 assigns fitness based on dominance strength and keeps an external archive of elite solutions. MOEA/D decomposes the multi-objective problem into scalar subproblems and solves them simultaneously with information exchange among neighboring solutions.

In this work, each solution represents two related components: the turbine layout and the cable routing. The layout defines which available positions are selected for turbine installation, while the routing defines the directed electrical connections between turbines and the offshore substation. Since cable feasibility and cost depend on the selected turbine positions, the routing structure must be considered during the search.

In the integrated approach, cable routing is handled during the evaluation step. For each turbine layout generated by the evolutionary algorithm, a sweep-based heuristic is applied to connect the turbines to the substation. This heuristic builds a feasible routing structure for the candidate layout, allowing each solution to be evaluated in terms of both energy production and cable cost. In this way, routing information is available during selection rather than being considered only after layout optimization.

We also evaluate an extended version in which evolutionary operators are applied to both the layout and the cable routing. Layout crossover and mutation modify turbine positions while preserving layout feasibility. Cable routing mutation introduces local changes in the routing structure. After mutation, feasibility checks or repair procedures are applied to preserve connectivity to the substation, avoid cycles, and prevent edge crossings.

Cable routing crossover combines routing information from two parent solutions. The offspring keeps the layout of one parent, while directed edges from the other parent

are inserted into its routing structure. Cable types are ignored during this step, since the objective is to transfer connection patterns between parents. After that, a repair step based on a minimum spanning tree is applied to rebuild a feasible routing, minimizing distances and avoiding edge crossings. Cable types are then reassigned according to the resulting tree and the capacity required in each branch.

The comparison between the integrated and extended versions allows us to evaluate two different ways of handling cable routing. In the integrated version, routing is generated by the sweep heuristic during evaluation. In the extended version, routing is directly changed by crossover and mutation and then repaired when necessary. This comparison helps assess whether it is more effective to guide the search with a domain-specific routing heuristic or to evolve cable routing structures directly.

5. Methodology

This section describes the experimental design used to evaluate the proposed algorithmic variants, covering the benchmark instances, quality indicators, statistical procedures, and parameter configuration.

5.1. Benchmark Instances

We used ten synthetic benchmark instances, labeled A through J, from the public dataset of [Cazzaro et al. 2023]. These instances simulate realistic offshore wind farm scenarios with multiple installation zones, varying seabed conditions, and a mix of pre-installed and optimizable turbines. The number of candidate positions ranges from 3,238 to 21,709, distributed across one to three zones per instance. Fixed turbines (10 MW) are excluded from optimization but contribute to wake effects. Mobile turbines (15 MW) constitute the decision variables. All instances share a common wind scenario based on real meteorological data [Netherlands Enterprise Agency (RVO) 2020]. Cable modeling follows [Cazzaro and Pisinger 2022a], using cables of 400 mm^2 and 630 mm^2 cross-section. Table 1 summarizes the key characteristics of each instance.

Table 1. Key characteristics of the benchmark instances. The last column lists the number of 15 MW mobile turbines per zone.

Inst.	Positions	Zones	Fixed	Mobile/zone
A	3,238	2	42	26, 8
B	6,989	1	15	99
C	7,098	2	8	60, 30
D	10,443	1	45	170
E	11,518	3	40	7, 94, 36
F	11,548	2	12	132, 26
G	14,637	1	35	140
H	19,498	2	40	158, 30
I	20,247	1	36	313
J	21,709	3	75	136, 74, 25

5.2. Quality Assessment and Statistical Analysis

Each algorithmic variant was executed in 30 independent runs per instance, with a stopping criterion of 100,000 objective function evaluations. Performance was measured using the hypervolume (HV) indicator [Bleuler et al. 2003, Knowles et al. 2006]. Before

computing the indicator, each objective was normalized to the range $[1, 2]$ and the reference point was set to $(0.9, 2.1)$. The HV values reported here represent the difference between each approximation set and a reference set obtained by filtering non-dominated vectors from the combined approximation sets of all variants. Lower values indicate better performance.

Statistical significance was assessed using the Kruskal–Wallis nonparametric test at $\alpha = 0.05$. When the omnibus test rejected the null hypothesis of equal performance, one-tailed pairwise comparisons were conducted between routing strategy pairs to identify which variant performed significantly better.

5.3. Parameter Configuration

All nine algorithmic variants were tuned independently using `irace` [López-Ibánez et al. 2016] under a budget of 400 candidate configurations. The parameters adjusted were the crossover rate (p_c) and the mutation rate (p_m). In our implementation, mutation is applied only when crossover is not executed, yielding an effective mutation probability of $(1 - p_c) \cdot p_m$ per individual. Table 2 reports the configurations selected by `irace` for each variant. All runs used a population of 200 individuals.

Table 2. Crossover (p_c) and mutation (p_m) rates selected by `irace` for each algorithmic variant.

Variant	p_c	p_m
NSGA-II-SEQ	0.41	0.08
NSGA-II-INT	0.27	0.10
NSGA-II-EXT	0.15	0.16
MOEA/D-SEQ	0.30	0.04
MOEA/D-INT	0.26	0.67
MOEA/D-EXT	0.33	0.99
SPEA2-SEQ	0.10	0.06
SPEA2-INT	0.70	0.89
SPEA2-EXT	0.49	0.27

6. Results

This section presents and discusses the experimental results. We first analyze the effect of embedding the sweep heuristic into the evaluation cycle, then compare the behavior of the three evolutionary algorithms and the extended routing strategy. Finally, we report the mean HV values and summarize the statistical outcomes.

6.1. Integrated versus Sequential Strategy

Table 3 presents the mean HV values for all variants across instances A–J. For NSGA-II, embedding the sweep heuristic into the evaluation cycle provides a clear advantage over the sequential approach. NSGA-II-INT obtains lower mean HV values than NSGA-II-SEQ in all ten instances. Considering the statistical comparison among the three NSGA-II routing strategies, NSGA-II-INT achieves significant wins in seven instances, namely

Table 3. Mean HV values across benchmark instances. Lower values indicate better performance. Bold entries indicate the minimum per instance across all nine variants.

Variant	A	B	C	D	E	F	G	H	I	J
NSGA-II-INT	**0.1812**	**0.1717**	0.1950	**0.1830**	**0.1837**	**0.1882**	**0.1791**	**0.1710**	**0.1864**	0.1879
NSGA-II-SEQ	0.2152	0.2040	0.2142	0.2038	0.2144	0.2066	0.1961	0.2042	0.2051	0.2213
NSGA-II-EXT	0.2089	0.1963	0.2076	0.1921	0.2018	0.1924	0.1917	0.1889	0.1993	**0.1801**
MOEA/D-INT	0.2120	0.2080	0.1955	0.2084	0.1960	0.1920	0.2105	0.1978	0.2191	0.1927
MOEA/D-SEQ	0.2130	0.2101	**0.1923**	0.2048	0.1961	0.1965	0.2099	0.1994	0.2219	0.1897
MOEA/D-EXT	0.2138	0.2097	0.1948	0.2071	0.1978	0.1941	0.2108	0.1987	0.2204	0.1921
SPEA2-INT	0.2147	0.2106	0.2191	0.2188	0.2278	0.2390	0.2137	0.2194	0.2382	0.2114
SPEA2-SEQ	0.1974	0.1811	0.1962	0.1983	0.2121	0.2119	0.1913	0.1966	0.2098	0.1915
SPEA2-EXT	0.2237	0.2063	0.1994	0.2011	0.2163	0.2264	0.1951	0.1992	0.2213	0.1847

A, B, C, E, G, H, and I. In instances D and F, no statistically significant difference is observed, while NSGA-II-EXT achieves the best result in instance J.

The mechanism behind this advantage relates to the quality of feedback available during search. In the sequential variant, layout optimization proceeds with no knowledge of routing cost, and the sweep heuristic is applied only once to the final population. In the integrated variant, cable routing costs influence selection at every generation, directing the search toward turbine configurations that balance both objectives. This results in a distinct search trajectory: the integrated variant explores solutions with higher energy yield even at higher infrastructure cost during the search, a trade-off direction that the sequential variant cannot explore by design.

Figure 1 provides a visual example of this behavior on instance A. The light-blue markers represent the initial approximation, while the orange markers represent the final front after 100,000 evaluations. The final approximation moves toward regions with lower infrastructure cost and higher energy production, indicating an improved trade-off during the search.

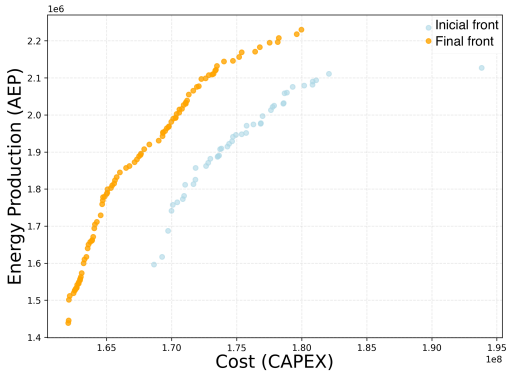


Figure 1. Pareto front evolution for NSGA-II-INT on instance A.

6.2. Algorithm Comparison

The three evolutionary algorithms respond differently to routing integration, indicating that the interaction between the routing strategy and the underlying search mechanism is an important factor in performance.

NSGA-II benefits consistently from the integrated strategy across most instances. Its dominance-based selection mechanism is well suited to exploit two-dimensional objective feedback, since Pareto ranking directly accounts for improvements in both energy production and cabling cost.

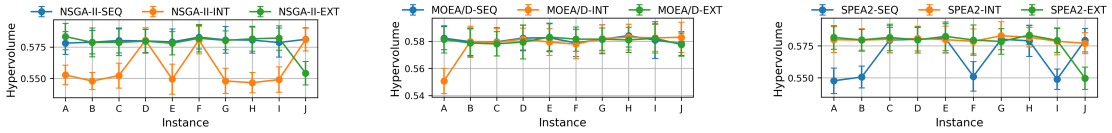
MOEA/D shows limited sensitivity to the routing strategy. The integrated variant achieves a statistically significant improvement only in instance A; no significant difference is observed in the remaining nine instances. This suggests that the decomposition-based search dynamics reduce the effect of routing-aware feedback. Scalar aggregation within fixed subproblem neighborhoods may limit the propagation of structural routing differences across the population.

SPEA2 exhibits the most variable behavior. The sequential strategy yields significantly better results in instances A, B, F, and I, while the extended strategy is preferred only in instance J. The remaining instances show no significant difference. SPEA2's external archiving and density-based selection appear sensitive to the frequent objective updates introduced by heuristic integration, which may reduce archive stability over time.

The extended strategy (EXT) achieves statistically significant best results only in instance J, the largest and most structurally complex benchmark, with 21,709 candidate positions and 235 mobile turbines distributed across three zones. In this setting, the sweep heuristic may impose constrained connection patterns. By directly evolving cable routing structures, the extended variant can explore alternative topologies that are less tied to the sweep construction, which appears beneficial when routing topology has a stronger influence on solution quality. In the remaining instances, the additional search complexity introduced by EXT outweighs its benefits under the given evaluation budget.

It should be noted that the EXT variant operates over a substantially larger search space, since both layout and routing structures are subject to variation, while all variants share the same budget of 100,000 evaluations. Part of its lower performance may therefore reflect slower convergence under a fixed budget rather than an intrinsic limitation of the formulation. Evaluating EXT under larger evaluation budgets is left for future work.

Figure 2 shows the mean hypervolume (HV) values obtained by the SEQ, INT, and EXT variants across instances A–J. Each panel reports the mean value over thirty independent runs, with one-standard-deviation bars. Since the reported HV values represent the difference between the approximation set produced by each algorithm and the reference set, lower values indicate better performance.



(a) NSGA-II variants (b) MOEA/D variants (c) SPEA2 variants

Figure 2. Hypervolume (HV) values with standard deviation for sequential (SEQ), sweep-integrated (INT), and extended (EXT) variants across benchmark instances A–J. Lower values indicate better performance.

Figure 3 shows the spatial distribution patterns produced by the three NSGA-II variants on instance A. Warmer regions indicate higher turbine density. NSGA-II-INT shows stronger spatial concentration, NSGA-II-SEQ produces a more diffuse distribution, and NSGA-II-EXT presents a more fragmented pattern.

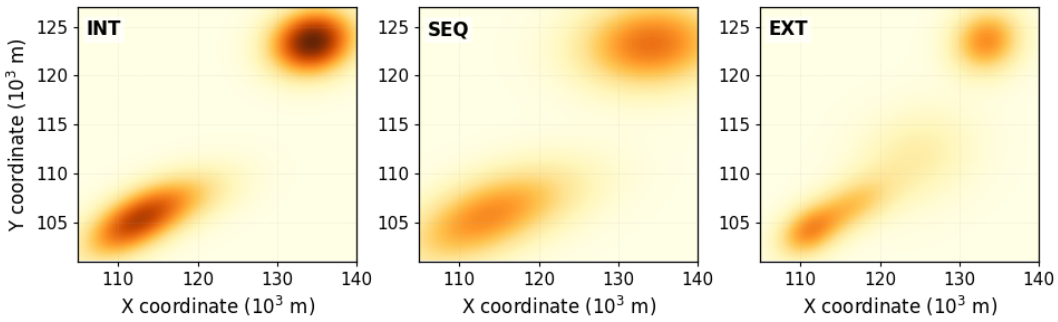


Figure 3. Kernel density maps for NSGA-II variants on instance A.

The statistical analysis was conducted with the Kruskal–Wallis test followed by one-tailed pairwise comparisons at $\alpha = 0.05$. Table 4 reports the best-performing routing strategy only when a statistically significant difference was observed. Cells marked with "=" indicate no statistically significant difference among the compared strategies.

Table 4. Statistical comparison summary.

Inst.	NSGA-II	MOEA/D	SPEA2
A	INT	INT	SEQ
B	INT	=	SEQ
C	INT	=	=
D	=	=	=
E	INT	=	=
F	=	=	SEQ
G	INT	=	=
H	INT	=	=
I	INT	=	SEQ
J	EXT	=	EXT

Overall, NSGA-II-INT achieves statistically significant wins in seven of ten instances and is not outperformed by the sequential variant in any instance. MOEA/D shows a significant difference in only one instance, with INT preferred. SPEA2 presents a different pattern, with SEQ winning in four instances and EXT winning in one. These results indicate that integrating cable routing information into the evolutionary search can improve solution quality, but its effectiveness depends on the interaction between the routing strategy and the search mechanism of the base evolutionary algorithm.

7. Conclusion

This work investigated three strategies for handling cable routing within multi-objective evolutionary optimization of offshore wind farms, combining NSGA-II, SPEA2, and

MOEA/D with sequential, integrated, and extended routing formulations across ten standardized benchmark instances.

The results show that embedding the sweep heuristic directly into the evaluation cycle improves solution quality, but its effectiveness depends on the base algorithm. NSGA-II-INT provided the most consistent performance, achieving statistically significant wins in seven of ten instances. MOEA/D was largely insensitive to the routing strategy, while SPEA2 performed better under the sequential approach in most cases. The extended strategy was advantageous only in the most structurally complex instance, suggesting that directly evolving cable routing structures becomes beneficial only when routing topology has a stronger influence on solution quality.

These findings suggest that the effect of routing integration depends on the interaction between the routing procedure and the underlying search mechanism. Since a single routing heuristic was considered, the results characterize the interaction between the sweep construction and the three MOEA architectures evaluated, and should not be generalized to other routing procedures without further evidence.

Several directions remain open. First, the study considered a single routing heuristic, so extending the comparison to alternative routing construction procedures would help determine whether the observed interaction patterns generalize beyond the sweep-based strategy. Second, adaptive mechanisms that switch between sequential, integrated, and extended coupling according to search progress could combine the strengths observed across different instances. Third, benchmarking the proposed strategies against a broader set of established and contemporary multi-objective algorithms, including implementations available in established optimization frameworks, would better position the results within the current state of the art. Finally, evaluating larger evaluation budgets, larger-scale instances, and real-world offshore scenarios remains important for assessing the practical applicability and scalability of the proposed approaches.

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